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LAK 16

Practitioner Track Proceedings

6th International Learning Analytics & Knowledge
Conference (LAK16)

University of Edinburgh, Edinburgh, UK
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Edited by
Rebecca Ferguson, Mike Sharkey and Negin Mirriahi



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INTRODUCTION

Practitioners spearhead a significant portion of learning analytics, relying on implementation and experimentation rather than on traditional academic research. Both approaches help to improve the state of the art. The LAK conference has created a practitioner track for submissions, which first ran in 2015 as an alternative to the researcher track.

The primary goal of the practitioner track is to share thoughts and findings that stem from learning analytics project implementations. While both large and small implementations are considered, all practitioner track submissions are required to relate to initiatives that are designed for large-scale and/or long-term use (as opposed to research-focused initiatives). Other guidelines include:

- *Implementation track record* The project should have been used by an institution or have been deployed on a learning site. There are no hard guidelines about user numbers or how long the project has been running.
- *Learning/education* related Submissions have to describe work that addresses learning/academic analytics, either at an educational institution or in an area (such as corporate training, health care or informal learning) where the goal is to improve the learning environment or learning outcomes.
- *Institutional involvement* Neither submissions nor presentations have to include a named person from an academic institution. However, all submissions have to include information collected from people who have used the tool or initiative in a learning environment (such as faculty, students, administrators and trainees).
- *No sales pitches* While submissions from commercial suppliers are welcome; reviewers do not accept overt (or covert) sales pitches. Reviewers look for evidence that a presentation will take into account challenges faced, problems that have arisen, and/or user feedback that needs to be addressed.

Submissions are limited to 1,200 words, including an abstract, a summary of deployment with end users, and a full description. Most papers in the proceedings are therefore short, and often informal, although some authors chose to extend their papers once they had been accepted.

Papers accepted in 2016 fell into two categories.

- **Practitioner Presentations** Presentation sessions are designed to focus on deployment of a single learning analytics tool or initiative.
- **Technology Showcase** The Technology Showcase event enables practitioners to demonstrate new and emerging learning analytics technologies that they are piloting or deploying.

Both types of paper are included in these proceedings. The technology showcases are identified by the word 'Showcase' at the start of their title.

Rebecca Ferguson, The Open University
Mike Sharkey, Blackboard
Negin Mirriahi, University of New South Wales

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Model Accuracy – Training vs. Reality

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Blue Canary is a higher education data and analytics company based in Phoenix, Arizona USA. We worked with a university to help predict at-risk students in their undergraduate degree programmes. Our model predicted attendance in a given week since we knew that missing a week of class was a proxy for attrition. The models were trained and selected using standard efficacy measures (precision, recall, F1 score). After using the models in production for six months, we saw that those metrics for actual data were fairly true to the training metrics. This validated the development of our predictive models.

DEPLOYMENT

The predictive model has been deployed to 100 faculty members teaching one of three different introductory courses in the university's bachelor's degree program. The faculty members access a set of visualisations and dashboards online. They are able to see the risk level of all of the students in their class, detailed charts on activity, historical information, and a conduit for submitting an alert ticket to be addressed by the institution's adviser

CONTEXT

At Blue Canary, we were asked by our client to build a predictive model for students enrolled in their online programme where classes typically last seven weeks. Since class duration was short, the sooner we could predict risk, the better chance we would have to assist the student. We decided to predict attendance for the week, since attendance was strongly correlated with attrition. We used the institution's definition of weekly participation as the basis for our prediction. What is the probability that a student would post a message to the online forum on four out of the seven days in a week?

PROCESS

We collect SIS and LMS fields from the institution to get historic data for training a predictive model. Historically, we know if the student did or did not meet the attendance requirements, so we have the outcomes needed to develop a model. From there, we split the data into three buckets: one bucket containing 70% of the data, which we will use to train the model, and two other buckets each with 15%, which we will use to test and validate the model. We then take specific fields that are important in identifying student behaviour to create features. These features are the inputs to the random forest machine learning modelling process. Originally, one predictive model was made for the entire seven-week course. This presented a problem however, because as students progressed through the course, the predictors of attendance change. Creating multiple models would result in higher accuracy rates. Therefore, we created seven different models, one for every week of the course. Now, though, maintaining seven different models proved to be difficult and we realized that by combining models from certain weeks together we can maintain a high level of accuracy while lowering the number of

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models. We finally settled on having two models (a Week 1-2 model and a Week 3-7 model) since the drivers of the model were similar at these thresholds.

MEASURING EFFICACY

To determine the accuracy of our machine-learning model we use the numerical values from a confusion matrix to calculate precision, recall and F1 Score. Using our scenario

- Precision is defined as: of the students we predicted would attend class that week, what percent actually attended?
- Recall is defined as: of the students who did attend class that week, what percent did we accurately predict?
- The F1 Score is simply the harmonic mean of precision and recall.

RESULTS

We went live with the predictions in April 2105. Every day, updated current data was fed into the predictive model to give a current attendance probability. These data were made available to faculty so they could intervene with students who were at risk of missing attendance. To test the validity of our model, we compared the actual weekly results against the accuracy of the initial training model. The results were as follows:

- Precision:

- Precision of Week 1-2 model from training: 84%
- Precision of Week 1-2 model in practice: 80%
- Precision of Week 3-7 model from training: 84%
- Precision of Week 3-7 model in practice: 84%

- Recall:

- Recall of Week 1-2 model from training: 91%
- Recall of Week 1-2 model in practice: 89%
- Recall of Week 3-7 model from training: 87%
- Recall of Week 3-7 model in practice: 84%

- F1 score:

- F1 of Week 1-2 model from training: 87%
- F1 of Week 1-2 model in practice: 85%
- F1 of Week 3-7 model from training: 85%
- F1 of Week 3-7 model in practice: 84%

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Getting Started with Learning Analytics: Implementing a Predictive Model Validation Project at North Carolina State University

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This session will present a practical strategy deployed at North Carolina State University (NC State) that allows institutions to explore the use of learning analytics without the complexity and risk associated with production implementations. At the heart of this strategy is a predictive model validation analysis in which historical data is ‘run’ through an open predictive model designed for general use in higher education. This approach sheds light on the effectiveness of the model and what implementation challenges may arise when larger scale deployment is undertaken. Presenters will share an overview of the strategy and analysis results.

DEPLOYMENT

During North Carolina State University’s first phase of their open learning analytics implementation, the goal was to use historical end-user data from approximately 1,500 students to evaluate the performance of an open predictive model previously developed by Marist College and deployed to over 2,200 students across four institutions. Using historical end-user data has allowed them to assess the accuracy, recall and false positive rates which has now been used to inform a ‘model tuning process’ to boost the predictive power of the model and prepare for ‘Phase II’ of their implementation.

GETTING STARTED WITH PREDICTIVE LEARNING ANALYTICS

Moving from talking about learning analytics to implementing learning analytics can be a challenge for any institution, given the complexity that can be involved from a technical, analytical and organizational perspective. Attempting to go from zero to a full institution-wide enterprise deployment overnight can often result in failed implementations that at best are embarrassing and at worst, turn the institution off completely to what can be a tremendously powerful tool for positively impacting on student success. This session will present a practical approach for getting started with predictive learning analytics while sharing outcomes from a recent implementation project.

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Over the 2013-14 academic year, North Carolina State University (NC State), a large research institution located in Raleigh, North Carolina, began an investigation into how best to deploy learning analytics, particularly an academic early alert system, across their multi-campus institution. As a result of this work the university concluded that taking an open-source approach would both fit well with its larger IT strategy (it is primarily a Moodle institution), reduce overall cost and facilitate sharing and collaborating with other institutions of higher education. Following a series of campus briefings and 'lunch-and-learn' sessions, designed to build consensus and identify strategic champions for an open strategy, the team decided to take a phased implementation approach that began by assessing the effectiveness of open predictive models and how well they would perform at NC State.

With this objective identified, Phase I of their implementation effort focused on a predictive model validation analysis project that was designed to shed light on how well generic models developed under the Apereo Open Learning Analytics Initiative would perform at NC State. The approach involved extracting relevant historical data from their Student Information System (SIS) and Learning Management System (LMS), preparing this data for analysis and then running the data through the previously developed open predictive model. The historical data used from NC State included:

- 1,691 unique student course combinations
- 1,587 unique students
- 42 unique courses

Based on initial research, high performing models from the Marist library were selected, customised to fit NC State's academic context for each algorithm and then deployed on the NC State ETL output. Multiple trials were run for each algorithm by introducing suitable randomisers and the reading for important metrics such as, accuracy, recall, FP rate, precision were tracked among other statistical metrics to deduce model performances. A mean value was calculated for trials for each of the prediction metrics for an algorithm and these results were tabulated.

FINDINGS

A summary of our findings will be shared at this session including:

- Overall, the predictive model portability results achieved were positive, presenting a good foundation to further the phased deployment at NC State.
- Using NC State historical data, the models have an overall accuracy of 75-77%. The models have retained most of the predictive power as compared to use at Marist College where the model was originally developed.
- The main goal of the model is to identify most of the at-risk population who need help fairly early in the semester. Recall metric is used to deduce model performance in this area. The recall rates achieved are by far the highest we have seen in populations other than Marist's, capturing approximately 88-90% of the at-risk population.
- The percentage of false alarms raised is approximately 25-26%, a result that requires further exploration in Phase II in order to find efficiencies to limit that number.

Taking a phased approach to their implementation had several advantages as it allowed the institution to understand the practical technical, policy and political challenges that can arise when working with such data without the pressure associated with managing a large scale enterprise deployment. More specifically, it allowed NC State to:

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1. Work with multiple divisions of the institution who oversee this data as a means to address data security concerns and technical issues related to the data extractions.
2. Develop relevant practical skills and knowledge among key staff ranging from database administrators to senior decision makers.
3. Customize the necessary Extraction, Transformation and Loading (ETL) processes needed to prepare data for the predictive model, which can then be re-used in future production deployments.
4. Develop a comprehensive Predictive Model Validation Report that assessed the performance of the model based on accuracy, recall, and precision criteria. This report not only helped the institution understand how well the model would work in the future, it also helped assess to what degree it may need to be tuned using historical data to boost its performance. Finally, it also acted as a communication tool to help institutional leaders fully to understand the potential benefits of the technology before making a major investment in it.
5. Set the focus and direction for the next phase of implementation, which involved tuning the open predictive model using local historical data from NC State.

This Practitioner presentation will provide an overview of the predictive model validation analysis approach as a means for institutions to get started with learning analytics. We will share the outcomes of the validation analysis implemented at NC State and a summary of lessons learned will be provided along with access to a range of open content, models and related technical resources that will allow others to replicate this approach at their own institutions.

Using Predictive Indicators of Student Success at Scale – Implementation Successes, Issues and Lessons from The Open University

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The Open University has deployed two predictive models to identify students at risk of drop out for intervention by their tutors and student support staff. This presentation will describe the deployment of the two models and outline the technical and cultural challenges experienced, along with the lessons learned. Additional application of the models will also be explored, including their use in aggregate to inform senior management of curriculum areas that might underperform and to help module leaders identify the pinch points in their learning designs.

DEPLOYMENT

The Open University has developed two predictive tools for providing indicators of student outcomes. One model uses data points available across the entire undergraduate curriculum and has been integrated into the university's Student Support Intervention Tool, making the predictions available for student support staff to use in selecting students for proactive support. The second tool, OU Analyse, provides a more granular analysis of student engagement on individual modules, and is adapted for each module's unique structure and learning design. This tool is being deployed on 11 modules in the 2015/16 academic year in pilot with individual tutors.

USING PREDICTIVE INDICATORS

The Open University (OU) provides distance learning undergraduate and postgraduate education to over 150,000 students through a model of supported open learning. Most of the undergraduate courses offered by the university have no entry requirements and therefore a large proportion of OU students start their study with lower than the standard entry qualifications for higher education in the UK. Courses are increasingly delivered through digital media, complemented by tutorial support offered by around 5,000 part-time OU Associate Lecturers through both online and face-to-face sessions. Each of those Associate Lecturers has a tutorial group of between 20 and 30 students that they support.

Learner support specialists organised in 17 curriculum-based Student Support Teams complement this individual support. As part of the university's learning analytics strategy, predictive analytics have been deployed to Associate Lecturers and Student Support Teams to identify students who may be in need of additional support. This presentation will describe the deployment of two predictive models, compare their different uses, outline the technical, staff guidance and cultural issues experienced in readying the predictive indicators for use and outline lessons learned.

The first predictive model deployed was developed by the university's planning office for the purpose of assisting with the forecasting of student re-registrations (Calvert, 2014). The model uses logistic regression to generate probabilities of individual students still being registered on their modules at key milestones, and of subsequently completing, achieving a pass and returning to study.

Probabilities are generated for every student on every undergraduate module, using a combination of

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30 demographic, student history and current study factors, each of which has been tested for its predictive ability. These probabilities have been integrated into the Student Support Tool, the system used by the Student Support Teams to identify students requiring an intervention. The teams work to a structured intervention strategy, including early contact with students on each module identified as potentially needing additional support.

In deploying the predictive indicators it was necessary to consider when the Student Support Teams might use them, and the guidance required to give staff unfamiliar with using the outputs of advanced analytics processes the confidence to use them in their student selection queries. A major part of the implementation was selling the use of the predictions through the use of accuracy statistics. It was also necessary to provide comprehensive instructions on how to use the probabilities, including a screencast video, and policy on the targeting strategy is currently under development. Technical implementation has been constrained to the existing functionality of the Student Support Tool. The actual use of the probabilities has similarly been constrained by existing work practices.

The second predictive model deployed is the 'OU Analyse' system developed by the university's Knowledge Media Institute (<https://analyse.kmi.open.ac.uk/>). The model uses machine learning methods to predict whether students will submit their next assignment during the module, based on student demographic factors and a fine-grained analysis of student behaviour based on virtual learning environment log data (Kuzilek, et al., 2015).

The predictions are presented through a dashboard application that can be made available to module leaders and also the Associate Lecturers directly supporting students, providing a weekly traffic-light indicator of whether the student is predicted to submit their next assignment. The OU Analyse model is nuanced to each individual module's learning design, and therefore has been piloted on 13 large-population modules during the 2014/15 and 2015/16 academic years.

Initial deployment of the OU Analyse tool has been via the module leaders and latterly by making the predictions available to Associate Lecturers. In both cases it has been necessary to provide guidance and support on how to use the predictions to prompt interventions with students. Associate Lecturers have used the information provided by the predictions in addition to the other management information they have at their disposal and their own personal knowledge of the student's progress.

The predictions have been used to prompt conversations with students about their study progress at an early stage, i.e. prior to the non-submission of an assignment. This has presented a challenge in gaining acceptance of the use of predictive indicators and a variety of pilot practices to evaluate. Technical challenges have been presented as the OU Analyse dashboard sits outside normal operation systems used by module leaders and Associate Lecturers. Piloting is on-going on modules that have started in October 2015 and formative evaluation of the pilots will be presented.

In addition to the deployments identifying individual students at risk and that might be targeted for intervention, alternative uses of the predictions have been explored. Using predictions in aggregate produces forecast numbers at each milestone and can help senior management identify particular areas of the curriculum that might be at risk of underperforming in a given year.

The use of aggregate predictions within a module has been used to identify potential 'pinch points' where higher levels of student drop out are experienced. Both of these potential applications prompt module leaders to consider changes to the learning design that might benefit future cohorts, and point

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to particular time periods in the current academic year where those pinch points might need careful management. These alternative uses will be explored in the presentation.

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The NTU Student Dashboard: Implementing a Whole-Institution Learning Analytics Platform To Improve Student Engagement

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The NTU Student Dashboard is a learning analytics solution designed to improve overall engagement by raising student and staff awareness about how students are engaging with their course. In 2013-14, Nottingham Trent University (NTU) piloted the Dashboard using the Solutionpath Stream tool. The findings from the pilot led to the institution-wide adoption of the Dashboard in 2014-15. Research at NTU demonstrates that student engagement measured by the Dashboard strongly correlates with both progression and attainment. This however, is only the first step in an on-going institutional change process.

DEPLOYMENT

After a successful 2013-14 pilot, the Dashboard is now in its second year of full institutional implementation. This means that all 28,000 NTU students have access to their own engagement data. Furthermore, another 1,500 academic and support staff can interact with the Dashboard. Students are encouraged to log in during induction and then periodically throughout the year and academics are encouraged to use it every time they have a one-to-one meeting with a student.

INITIAL PROJECT OUTCOMES

The Dashboard was developed to encourage greater student engagement with their course. The institution was also interested in testing three potential benefits, its use to:

- improve student retention
- increase students' sense of belonging with their course communities, particularly with their tutors
- improve academic attainment.

The Dashboard measures student engagement using a range of measures: engagement with the VLE, entry to academic buildings using swipe cards, library use and coursework submission. It provides students with a weekly engagement score (from high to low) and raises alert emails to tutors when students have no engagement with any measures for 14 days.

A project team was set up under the leadership of the PVC Academic comprising academics, IT specialists, students, support specialists and experts in matters such as student data and ethics. Over time, this group has been formally enmeshed within the institution's academic governance structures.

LESSONS LEARNT FROM THE IMPLEMENTATION

NTU ran a pilot year in 2013-14. The primary goals for the pilot were to test technical integration of the different University data systems with the Solutionpath Stream tool and equally to test students and staff reactions to using the resource. The evaluation of the 2013-14 data demonstrated that the tool

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worked as it should, and that both students and staff felt that there was sufficient utility in the information provided to implement the Dashboard across the whole institution (Foster, Kerrigan & Lawther, 2016, forthcoming).

There was a strong association with student engagement measured in the Dashboard and both progression and attainment. For example, in 2013-14 only 24% of first year students with a low average engagement progressed from the first to second year, whilst 92% of students with a high average engagement progressed. At the time of writing, we do not have overall engagement data for the 2014-15 academic year. By the time of the conference, we will have this data and share our analysis of comparisons between the years.

We are starting to see changes in institutional behaviours. In surveys during the 2014-15 academic year, 27% of students had changed their behaviour in response to the data provided by the Dashboard (n=482) and 61% of staff found the Dashboard useful and perceptions of usefulness increased with greater use (n=140).

During the whole institutional implementation (August / September 2014) the key lessons learnt were associated with the real-world operation of the Dashboard: staff communication, training, overcoming genuine concerns about abuse of power and privacy. The key factors for success have included the importance of having a multidisciplinary team to implement the project. Clearly, technical and project management expertise from the Information Systems department have been crucial, but this project has only succeeded because both student and academic end users are well represented in the project team.

At the time of writing, it is clear that the learning analytics tool works as it was expected to. It provides both staff and students with a useful and usable measure of engagement. However, it is also clear that institutional change is a more far reaching and more complex project. As the project team moves through the next phases of the Dashboard project, there will be increasing focus on how the institution uses the data to change operational practice whilst still leaving responsibility for students to remain in charge of their own learning.

This work will be furthered by NTU's involvement in the Erasmus+ funded ABLE Project (2015-2018) conducted in partnership with KU Leuven and U Leiden to explore further how institutions use the data provided by learning analytics to improve student engagement, retention and success.

How CRS Deployed Watershed LRS and xAPI To Evaluate the Effectiveness of Training for Disaster Response Teams

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The Catholic Relief Services (CRS) Emergency Response and Recovery programme sends teams to serve in areas that have been hit by disaster, such as an earthquake, flood or tsunami. CRS has trained 3,300 of the first responders sent to these areas since 2009. But how effective is that training when these teams arrive in some of the most challenging environments on earth? This presentation will explore how CRS deployed Watershed LRS to capture data about both learning and job performance via the xAPI. Find out how CRS use this data to evaluate and improve their training provision and become more effective.

DEPLOYMENT

This project involves analysis of training and performance of first responders to major emergencies to which CRS responds. Tracking of the training is fully deployed and underway, but tracking of performance relies on there being a major emergency, such as an earthquake, flood or tsunami to which CRS responds. Until such an emergency occurs, we will not see full deployment of the performance tracking elements of the project and the results of how effective the training is. Of course, nobody is hoping for a disaster to happen!

CRS EMERGENCY RESPONSE AND RECOVERY

Catholic Relief Services was founded in 1943 by the Catholic Bishops of the United States to serve World War II survivors in Europe. Since then, the organisation has expanded in size to reach almost 100 million people in 93 countries on five continents.

CRS's mission is to assist impoverished and disadvantaged people outside the United States, working in the spirit of Catholic social teaching to promote the sacredness of human life and the dignity of the human person. Although the organisation's mission is rooted in the Catholic faith, its operations serve people based solely on need, regardless of their race, religion or ethnicity.

The CRS Emergency Response and Recovery programme sends teams to serve in areas that have been hit by disaster, such as an earthquake, flood or tsunami. CRS has trained 3,300 first responders sent to these areas since 2009.

The work carried out by CRS is really important – the stakes in helping disaster survivors could not be higher. With a ticking clock, it is also urgent work and teams need to get on with the job quickly and effectively in a range of different situations, cultures and challenges. The work is hard physically, emotionally and spiritually. For all these reasons, effective training is vital to CRS. The organisation needs to be confident that the teams it is sending are prepared in the best possible way; it needs to be confident that its training works.

CRS training includes classroom training, choice-based simulations created in Articulate Storyline and

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LMS courses (Cornerstone On Demand). The simulation is completed before and after the classroom training as an assessment of distance travelled. The simulation provides an introduction to what CRS: <http://learningninjas.com/clients/crs/mktg/story.html>

All the training is completed by teams prior to deployment to a disaster area. On deployment, team members complete self-assessments and are observed by a third-party assessor who completes a performance impression checklist.

CRS worked with Watershed to outfit each of these elements with xAPI tracking (face-to-face elements are tracked using observation checklists). By following the xAPI specification for their tracking, CRS was able to integrate with an existing learning analytics platform, in this case Watershed LRS. The organisation could take advantage of existing code libraries and benefit from the thought, debate and experimentation that has been put into xAPI and the way tracking works.

Having the data in this common format also means that the organisation can reuse the data in future reports either within Watershed, created in house or perhaps provided by other vendors.

The self-assessments and performance observations are carried out in areas that have been hit by a disaster. Internet access is likely to be non-existent or very limited. For this reason, tracking data was stored offline on a mobile device and synced back to the Learning Record Store when a connection became available. xAPI is specifically designed to be compatible with data captured, stored and synced in this way.

Watershed is a learning analytics tool that organisations use to collect data from a range of sources. They then visualise this data via various reports specifically designed for learning. Reports are used to monitor activity, usage and progress, explore correlations and relationships and evaluate learning resources and programmes.

The data from CRS's various training and performance observation data sources is collected together in Watershed. Elements are reported on both individually and together. Data from the simulation tasks, for example, is used to explore which steps are completed incorrectly most often so that additional training can be focused on those areas. The reports even go into detail about how people responded incorrectly, so in a task involving selecting team members, a report tells the analyst which team members are most and least commonly chosen. The simulations use branching, CRS-comparing paths taken by different learners and the points associated with those particular paths.

Tracking of the simulations is especially important since emergencies are rare. This data allows CRS to identify common trip-ups much more quickly so they can modify classroom and pre-deployment training to better prepare responders before the next disaster happens rather than afterwards.

One challenge identified by the CRS team was in designing a meaningful user interface for their branching simulation. In their simulation there is one correct path. Learner decisions can cause them to deviate from that path by either being too forceful or too relaxed in interactions with the local agencies representing in the simulations. The final visualisation shows each learner's path as a line that can deviate to the left and right of a central line representing the correct path. In discussing this project with us, CRS emphasised the importance of carefully planning and testing visual reporting to ensure it meets requirements.

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Another challenge of this project was associated with the limitations of xAPI reporting in the tools used. CRS worked with us to add additional tracking to their Storyline courses in order to capture the data required to support their reporting needs.

CRS identified five lessons learnt from their project:

1. It is hard to explain this kind of project to a stakeholder; make a demo.
2. Deciding what data you need to capture is hard; think carefully about how to get the best data and what will have the highest value return.
3. It is OK if you do not understand everything; get help.
4. Complex analytics from multiple sources are achievable.
5. Pilot projects are great. Start small and build from there.

How CUES Deployed Watershed LRS and xAPI To Track and Analyse Continuous Learning

Andrew Downes

Watershed

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The Credit Union Executives Society (CUES) is an international membership association dedicated to the education and development of credit union chief executive officers (CEOs), directors and future leaders. CUES provides resources to its members including learning materials on its learning management system (LMS) and content on its website. Members also learn from external resources across the Internet. This presentation will explore how CUES deployed Watershed LRS to capture data about members' learning via the xAPI. This data includes tracking of LMS, website and third-party content. Find out how CUES is using this data to inform its member engagement initiatives and provide the best possible services.

DEPLOYMENT

CUES has 13,000 member organisations across the United States, Canada and the Caribbean. Since the Watershed implementation launched in October 2015, over 400 member organisations have registered and used the system to track progress of over 40,000 learners. Feedback has been great, and CUES expects increased user count once full promotion begins to member organisations.

Activities performed by learners on the CUES content portal are automatically tracked in Watershed, and credit union managers can monitor progress through aggregated data in dashboards. Managers are also able to monitor training performance by seeing scores on a wide variety of assessments given to learners.

CREDIT UNION EXECUTIVES SOCIETY (CUES)

CUES is an international membership association dedicated to the education and development of credit union CEOs, directors and future leaders. CUES provides a range of resources to its members, including learning materials on its LMS and content on its website. Members also learn from external resources across the Internet.

CUES already tracked usage of LMS content, but had no information about member usage of website resources and third-party content. Getting this data was important to CUES in order to inform member engagement initiatives. For CUES, it is important that members are engaged with the content and services the organisation provides so that members get a good service and renew their membership. It is also important to CUES that members can log in and see usage data and LMS scoring data in one place.

CUES worked with Watershed to outfit its website with xAPI tracking. This includes use of the magazine, online courses, research library and online videos. It includes both classroom training and informal learning. CUES also deployed a bookmarklet created by Watershed LRS, which members can add to their browser. Members click this button to record web pages from which they have learnt.

By following the xAPI specification for tracking, CUES was able to integrate with an existing learning analytics platform, Watershed LRS. The organisation was able to take advantage of existing code

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libraries and benefit from the thought, debate and experimentation that have been put into xAPI and the way tracking works. Having the data in this common format also means it is possible to reuse the data in future reports either within Watershed, created in house or perhaps provided by other vendors.

Watershed is a learning analytics tool that organisations use to collect data from various sources. They then visualise this data via various reports specifically designed for learning. Reports are used to monitor activity, usage and progress, explore correlations and relationships and evaluate learning resources and programmes.

CUES analyses its data in Watershed using reports that provide insights about:

- Most and least active learners, enabling the organisation to identify how engaged members are.
- Most and least popular content items, enabling the organisation to promote good content and rework poor content.
- Most and least popular content types (for example videos and blogs.), enabling the organisation to better plan future content development.
- Learning paths, enabling the organisation to see how learners move through its content and use this information to improve its information architecture.

The CUES project also faced some technical challenges. As part of the project, organisational and relationship data about 10,000 learners was loaded into Watershed ahead of launch. This was the largest collection of data of this type that had been loaded into Watershed at that time and was also of an unusual structure in terms of the size and number of groupings. Watershed was unable to cope and the CUES implementation had to be shut down for a short time whilst our developers worked through the challenge. We were able to bring the site back up quickly, thanks both to the work of our developers and the flexible infrastructure provided by Amazon Web Services. This incident highlights the importance of testing and pilots prior to going live with a large number of users. If we had not done that in this scenario, the problem would have manifested at launch and had a much greater impact. Watershed is now well able to handle this volume and structure of data (and significantly more) for future projects.

One challenge CUES initially faced was that of learner uptake for this project, with only 80 users registered. CUES has since increased this to over 400 member organisations registered and over 40,00 learners. This was achieved through additional press releases and emails about the project, including positive testimonials from a small group of pilot users, and by working with us on product improvements based directly on feedback from members.

Learner uptake is inherent in member organisations like CUES where participation in any initiative is not mandatory. Indeed, improving member uptake of resources is one of the goals of the project. The data gathered will enable CUES to optimise its content for members, driving improved uptake.

As a next phase of work, CUES is already considering adding additional data sources relating to face-to-face events. This includes events run by CUES, and it is also exploring ways to enable members to record details of attendance at external events that are relevant to their professional development.

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Going Enterprise: Challenges Faced and Lessons Learned When Scaling and Integrating Research-based Product for Commercial Distribution

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This presentation explores some of the challenges faced by researchers when tasked with implementing a research-based product for large-scale distribution. We divide these challenges into three categories: presentation-layer, methodology, and back-end infrastructure and architecture. Using our own experience as an example, we explain the rationale behind the decisions made and look at how they were implemented in practice. We finally provide some guidelines for a successful transition from pilot project to enterprise solution.

DEPLOYMENT

X-Ray Analytics was re-architected for massive deployment in the Moodlerooms eco-system. Three instances with a total of over 20,000 courses and more than 300,000 enrolments were chosen for stress-testing the system and validating the methodologies used.

X-Ray Learning Analytics is a software package that analyses information from the learning management system (LMS) to provide reports, forecasts/predictions and recommendations to instructors and administrators. Prior to 2015, the software was chiefly used in research settings and pilot projects, now we were charged with the task of turning the application into a scalable, integrated and enterprise grade solution for massive distribution among Moodlerooms' client base. Ideally it should be turn-key and depend as little as possible on the scarce data-science resources available in the organisation. Going Enterprise presented us with a series of challenges in terms of (a) the presentation-layer, (b) methodology and (c) back-end infrastructure and architecture.

PRESENTATION LAYER

Of the more than 80 reports and visualisations available in X-Ray, 34 were chosen for integration into

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the Moodlerooms implementation. The integrated approach meant switching from a web-based front-end with separate login and browsing access to the reports, to a web-services-based system where analyses are delivered in context within the LMS. Nomenclature had to be changed to ensure intuitive understanding by non-technical users, and several of the visualisations had to be redesigned to support large enrolment courses of more than 200 students, a scenario which had not been encountered during the pilot stages of the project.

In order to comply with company policy as well as the USA's Section 508 accessibility requirements, all visualisations needed to be friendly to users with colour-deficient vision as well as screen-reader accessible. The latter was particularly counter-intuitive to the data-scientists since the *raison d'être* of most visualisations in statistics is that the underlying data-points do not effectively reveal patterns when displayed as tables and lists.

METHODOLOGY

Deploying X-Ray at scale also presented methodological challenges. During the research and development stages of the project we had typically been afforded the luxury of cherry-picking appropriate courses for analysis in tight collaboration with researchers and stakeholders at the relevant institutions. The development of risk-models and elicitation expected values for triggers throughout the system was based on the data-mining a specific subset of courses with ample heuristic input. This was clearly not a viable approach given the scale intended for commercial distribution.

The main problem we encountered when exploring the Moodle instances available in the client-base was extreme heterogeneity in how the LMS is used. Even within the same institution we found that some courses were conducted as all-online courses while in other cases Moodle was simply used as a document repository. As a result we developed an on-boarding procedure and application that carries out a preliminary data-mining exercise, filtering out courses and users whose activity level is such that they are not suitable for creating baseline parameters.

We also developed a Time Machine Application, which simulates the implementation of X-Ray for a past semester and allows for analysis of the results and manually updating the trigger settings and/or risk models. These procedures still require some human input, both from the data scientists and the institution, but we were able to automate and streamline the most time-consuming components to a level deemed viable for the purpose.

BACK-END INFRASTRUCTURE AND ARCHITECTURE

Deploying X-Ray within the Moodlerooms eco-system involved making it available on a cloud-based architecture. This was necessitated by operational and cost-management considerations as well as legal constraints that in some cases (for example, Germany) prohibit moving student data outside the borders of the country, so the application needed to run in a local data centre.

During the research and development and pilot phases of X-Ray most analysis had been performed on whatever was readily available to the researcher in charge. This sometimes meant the researcher's laptop, a setup that was clearly not reasonable for the context. Luckily the researchers were already using Amazon Web Services (AWS) for several of the system components, often running entire analyses in the cloud-base since this provided superior computing power.

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All the X-Ray analyses are implemented in R (the largest open-source programming language for statistical computing), so switching to an all AWS-based system did not in itself prove particularly challenging. The fact that almost everything needed to run largely unsupervised turned out to be more of a problem. In a supervised set-up if a report was not produced, or an analysis did not finish, we could take manual measures to continue analysis and restart the processes that had failed.

The initial architecture depended on the largest machine instances available on AWS with several analyses running in parallel on each of the 32 cores (the maximum available) of the same instance. The problem with this approach was that if one of the threads stalls – whether due to bugs in the computer code or hardware failure – this could compromise the entire system. Furthermore the post-mortem analysis was exceedingly difficult since tracking down any problem required manually scrutiny of log-files corresponding to as many as 32 different processes and hundreds of courses.

We therefore opted for the opposite approach: instead of one large instance handling several analyses we decided to use several small instances each handling one analysis at a time. We architected a work-order system through which each instance of the X-Ray Analysis Server running in the cloud fetches a work-order at a time, performs the analysis and then fetches the next – until none are available, in which case the instance shuts itself down. AWS auto-scaling tools allow instances to be automatically added as needed, and when an instance stalls the issue is contained to a single box, not compromising the overall running of the system and facilitating the post-mortem analysis.

CONCLUSIONS

Practitioners wishing to provide enterprise-scale solutions need to be wary of the many challenges this poses. Most of these are relatively easily mitigated and, if addressed early in the design process, can be avoided altogether along with the need for substantial refactoring and/or re-architecting.

Learning analytics dashboard for improving the course passing rate in a randomized controlled experiment

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The intention of this study was to increase the number of students passing a Java programming course by giving feedback on their online behaviour through a learning analytics dashboard. The treatment consisted of a randomized controlled experiment with 556 students. Of these, 276 students received for eight weeks an email with a link to their dashboard and 280 students were assigned to the control group. The treatment and control groups are comparable on the analysed characteristics. There was no significant difference in withdrawal between the control and treatment group. The results show that offering the dashboard had no significant effect on the percentage passing and the exam marks. The analysis of the use of Myprogramminglab showed that the treatment group practised 5% more than the control group. This result is significant at $p = .1$. There was a significant difference between the online activity of students in the academic year 2015 and that in 2014. In 2014, online activity was much higher than in 2015.

INTRODUCTION

For computer science students at the Amsterdam University of Applied Science (HBO-ICT) in Amsterdam, 'Programming' is a first-year 10-week course of Java programming. The course is supported by a number of e-learning systems including the Myprogramminglab of Pearson¹ and the Moodle² environment. The classes were designed according to the 'Flip the Classroom' (Davies, Dean, & Ball, 2013) principle. At home the students prepared their lesson by taking online quizzes and exercises.

At the end of the course in week 10 the students are tasked with programming a small Java program and are then graded on the results of their efforts. The results of the programming course were insufficient, about 42%, instead of the desired 30% of the students $n=1217$ failed in 2013 and 2014. The activities of the students in e-learning environments tend to be predictable for results on the course (Hu, Lo, & Shih, 2014; Tempelaar, Rienties, & Giesbers, 2014). The analyses of the online behaviour in the population of 2014 $n=684$ showed that there was a correlation between online behaviour and the result of programming. Students who did all the online exercises scored an average of 6.8 ($SD=2.7$) and the ones who did not scored an average of 4.8 ($SD=3.5$) ($t(682) = -7.84$ $p < .000$). These results led to the development of an learning analytics dashboard displaying information about how well the students perform on their online task and the predicted result and chance of passing the course.

¹ <http://www.pearsonmylabandmastering.com/northamerica/myprogramminglab/>

² <http://moodle.org>

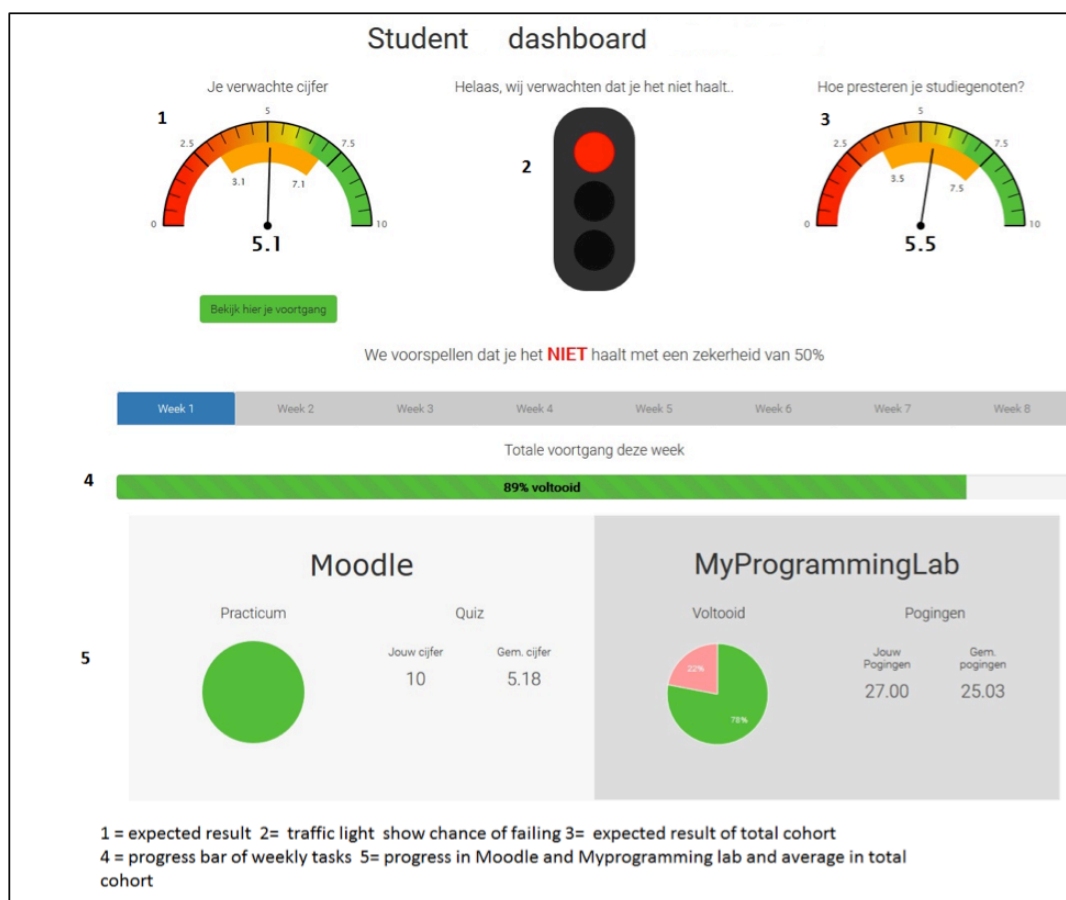


Figure 1. Student dashboard for Week 1

The purpose of the dashboard is to encourage the students to finish their online tasks. The effectiveness of a learning analytics dashboard is examined in the paper by (Lauría, Moody, Jayaprakash, Jonnalagadda, & Baron, 2013). This article gives the effect of the use of a so-called Early Warning system (EWS) on the study results. An EWS is used to identify high-risk students in a course (Hu et al., 2014) as early as possible with the aim of changing their learning behaviour. The students in courses with an EWS achieved on average a 6% higher final grade than the control group. An effect of the system is, that of the treatment group a larger group withdrew from the course: 25.6%, compared to 14.1% of the control group.

The Learning Analytics dashboard (Figure 1) was implemented on a weekly basis. The dashboard visualized the expected result and risk of failure for the student. For the expected result, linear regression models are used, and for the risk of failure decision tree algorithms (Decision Stump, Adaboost) (Hu et al., 2014) are used. These models were created through WEKA 3.6. The failure risk models in week 8 correctly classified 88.8 % of the instances (607), 11.2% of the instances are incorrectly classified (77). The expected results are calculated with linear regression models of WEKA³. In week 8

³ <http://www.cs.waikato.ac.nz/ml/weka/>

the model has a $R^2 = .41$. The dashboard application was developed in PHP⁴ with a MySQL⁵ database and the prediction models were used in Kettle⁶ to generate the predictions. A Perl script converted the data from Moodle and Myprogramminglab into Excel files. The Excel files are imported in SPSS and uploaded to the MySQL database of the dashboard application. The dashboard application generated the dashboards on the basis online behaviour data and the generated predictions (Figure 2).

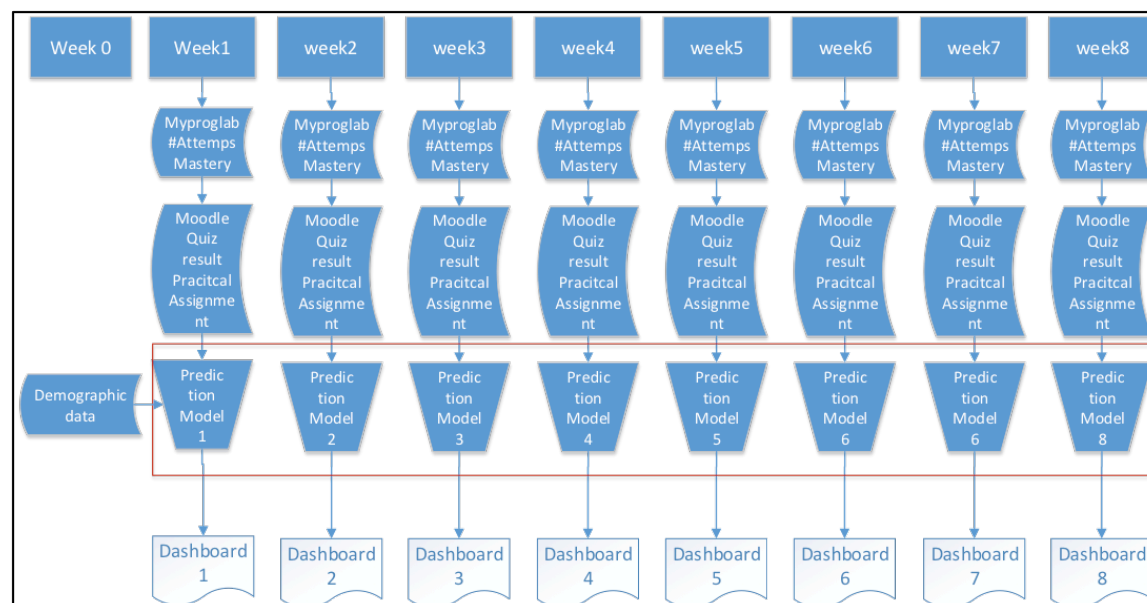


Figure 2. Visualization of dashboard generation

The treatment with the dashboard took place during the programming course in the first 10 weeks of the academic year 2015-2016. The exam was on 2 November 2015 and the retake on 10 December 2015. The course is taught all computer science freshmen ($n = 558$) and given by 14 different teachers to 20 classes. The students had two lessons of two hours per week. This study gives insights into how a learning analytics dashboard has an effect on the student success rate in a programming course. Another contribution is that it shows if the dashboard has any effect on the online behaviour. This leads to the following research questions:

1. Will the learning analytics dashboard improve the success rate and the results of the students participating in the Java programming course?
2. Will the learning analytics dashboard increase the online activities of students?

⁴ <http://php.net/>

⁵ <https://www.mysql.com/>

⁶ <http://community.pentaho.com/projects/data-integration/>

RESEARCH METHOD

The study is set up like a RCT and 556 students are involved in the experiment, with 276 in the treatment group and 280 in the control group (Figure 3). From previous cohorts (2013, 2014) it was known that the results of programming differ according to the specialization of the student. To achieve internal validity of the experimental design, the students were conditionally randomized per their specialization. The students from the treatment group received a mail with a link to their dashboard every week. In total the students received eight mails with a link to their dashboards. At the end of the course, the results of the exams were collected for both the treatment and control group.

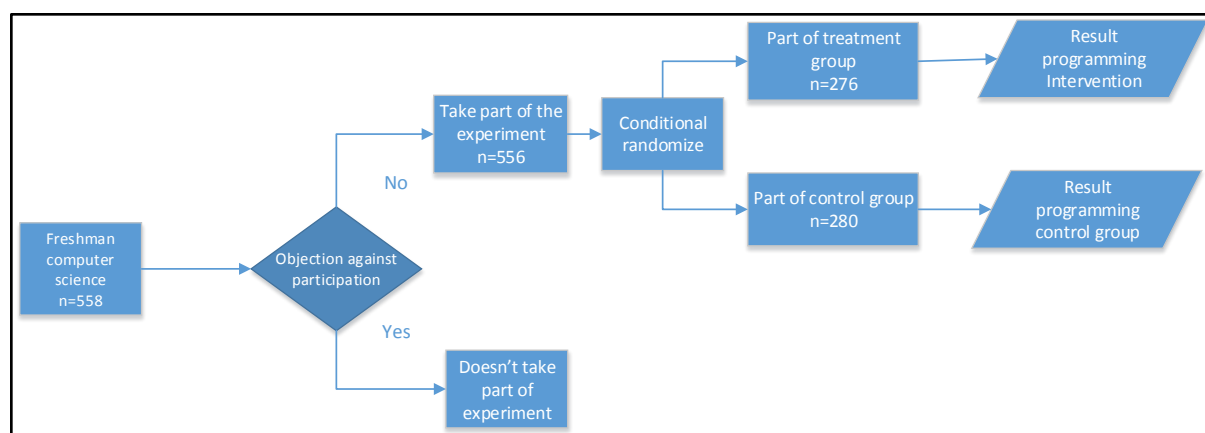


Figure 3. RCT setup for dashboard treatment

RESULTS

In this section, the results of the exams are evaluated. The article (Lauría et al., 2013) gave rise to analysis of whether the use of the dashboard had an effect on not participating in the exam. In Table 3, cross tables of the exam results are given. It indicates that 100 students of the total cohort ($n = 556$), which is 18%, did not take any exam. Between the means of the treatment – and control group there was no significant difference on whether or not to withdraw from the exam (Table 1).

Table 1. Means of students taking part of the exam: treatment and control group

	Control	Dashboard	n
Exam	.509	.491	456
No exam	.504	.496	100
Total	.505	.496	556

$$\chi^2(1) = 0.27 \text{ } p=0.602$$

The effect of the dashboard treatment on passing the programming course is shown in Table 2, where the means of passing the exams for the treatment and control groups are shown. This shows that for the treatment group there is a small improvement in the percentage passing at the first exam, which is not significant.

Of the entire cohort of 556 students, 332 passed the programming course. This is 59.7%. Of the 456

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students who took the exam, 72.8% were successful.

Table 2. Means of passing: treatment and control group

Result	Control	Dashboard	n	p	χ^2
First exam passed	.523	.533	228	.830	(1) .5
Retake passed	.155	.519	116	.599	(1) .28
All exam passed	.741	.714	456	.516	(1) .42

n=556. Missing =100. Passed: 332 Failed= 124

Table 3 shows the means of the grades of the exams. The marks are displayed in (0-100). The results in Table 3 show no significant differences between the control and treatment group.

Table 3. Means and standard deviation of the grades of the treatment and control group (n=556)

		n	M	SD	p
First exam	Control	220	57.95	28.91	.83
	Dashboard	212	57.38	27.45	
Retake exam	Control	110	57.53	26.06	.87
	Dashboard	106	56.92	26.71	
All exams	Control	232	68.62	24.91	.42
	Dashboard	224	66.71	25.13	

CONCLUSION

This study tried to increase the number of students passing a Java programming course by giving feedback on their online behaviour through a learning analytics dashboard. The treatment consisted of a randomized controlled experiment with 556 students, 276 students received for eight weeks an email with a link to their dashboard and 280 students were assigned to the control group. There was no significant difference in withdrawal between the control and treatment group. The analyses have shown no significant effect of offering the dashboard, on either the percentage passed or the mark of the exam.

An important aspect of the dashboard intervention is the use of the online environments by the students. The analyses of the online use did not provide any significant differences between the control- and the treatment group, although a small effect is found at Myprogramminglab exercises. Students from the treatment group passed about 5% more exercises on a significance level $p = .1$. The analysis showed that online activity strongly declined over time. This was due to the flip-the-classroom principle being no longer compulsory. In the academic year 2015 the students practised online significantly less compared to those in the academic year 2014. The dashboards will only be able to predict well if the student practise in the online environments, otherwise the dashboard will predict very badly. This may cause the low interest of the students in the dashboard at the end of the course. Maybe the dashboard should be incorporated in courses where a part of the course result is determined in the online environments. In these courses the students will practice more and the dashboard will be more functional.

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Showcase

Deeper Understanding: Transitioning from Academic to Learning Analytics in UK State-Maintained Secondary Education

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The demonstration will present the journey from academic analytics to learning analytics in Bright Tribe Trust (UK) academies. The showcase will focus on the application of free, low cost and emerging tools to enable learning analytics in state-maintained secondary schools. Using a demo dataset, delegates will be able to trial the tools using their own device or one of 30 which will be provided. The presentation will also highlight design considerations for implementation at scale, lessons learnt through the pilot phases, solutions for collaboration and sharing, and a discussion of the ethical considerations in a UK K-12 context.

DEPLOYMENT

The initial deployment of the analytics suite took place during the final term of the 2014/2015 academic year. Bright Tribe Trust is a UK Multi-Academy Trust, supporting 13 institutions at the time of writing. The pilot was run in The Whitehaven Academy, Cumbria. Within this Academy, the 'Technology Supported Learning' pilot focused on one Year 9 class of 13- and 14-year-olds across three curriculum areas: English, Science, and ICT. Following this successful pilot, Bright Tribe has started implementation activities to roll out to secondary phase schools for pupils aged 11–19 and a University Technical College during the 2015/2016 academic year.

ANALYTICS IN SCHOOLS

Bright Tribe Trust is a multi-academy Trust currently comprised of 13 Primary (for pupils aged 4–11) and Secondary Schools across the UK. The initial focus for the Trust was on garnering meaningful and consistent academic analytics for all of the schools in its estate in order that key performance indicators (KPIs) could be tracked and monitored effectively at school and Trust level. The context within which these analytics are produced is one in which progress measures and indicators for schools must reflect Department for Education (DFE) requirements, Life without Levels (which removed the statutory need to assess against a defined level and points scale across all education phases) and Progress 8 measures (which define the progress a student makes across eight subjects in relation to a target based on a population average of similar prior attainment).

However, it is recognised that the academic analytics alone will not impact on performance outcomes for pupils. Therefore, the Trust is now testing tools, methodologies and approaches to produce

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meaningful learning analytics that will inform and support interventions to improve teaching and learning outcomes.

The Whitehaven Academy is the focus for the pilot work. With 850 students on roll, the Academy has experienced significant changes in the two years since it was taken on by the Trust, including three changes of Principal. GCSE and A-Level results (subject-specific qualifications typically taken by pupils aged 16–18) in 2015 were disappointing and the Academy and Trust want to break the spiral of failure.

The class that was selected for the pilot was a Level 5 (above average attainment) group who were taught English, Science and Computer Science together. This allowed for cross-subject comparison of outcomes and experience.



Figure 1. Year 9 students with pilot devices

CHALLENGES

There are challenges and constraints that are specific to K-12 education in the UK (but that are likely to be common in K-12 settings worldwide) that influence the technology strategy and approach taken towards learning analytics.

Life Without Levels has effected a fundamental change to formative and summative assessment across all Key Stages (the blocks of years into which the UK National Curriculum is divided): the pilot and on-going work are taking place during a time of transition and flux within academic analytics for schools.

Methods of data collection and collation for use in learning analytics are frequently aided by access to computing resource and are ideally situated in a 1:1 student device context. This is problematic for the majority of primary and secondary phase schools where device ratios more typically range from 1:3 through to 1:10. This gives rise to considerations on getting to scale through parent-supported 1:1 schemes, or opening up to Bring Your Own Device (BYOD).

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Life without Levels

In March 2014, the UK Department for Education (DfE) published information for schools on the National Curriculum and assessment from September 2014. The document says that level descriptors will be removed from the National Curriculum and will not be replaced. It adds: 'Schools have the freedom to develop their own means of assessing pupils' progress towards end of Key Stage (KS) expectations.'

The DfE ran a consultation on primary assessment and accountability measures under the new National Curriculum in the summer of 2013. With respect to forms of assessment, the consultation document says: 'There will be a clear separation between ongoing, formative assessment (wholly owned by schools) and the statutory summative assessment, which the government will prescribe to provide robust external accountability and national benchmarking.'

In April 2014, the DfE published guidance on assessment principles to help schools implement new arrangements for assessing pupils' progress. It explains: 'Schools will be expected to demonstrate (with evidence) their assessment of pupils' progress, to keep parents informed, to enable governors to make judgements about the school's effectiveness, and to inform Ofsted inspections.' The guidance outlines three principles of effective assessment systems. It says such systems should:

- Give reliable information to parents about how their child and their child's school is performing
- Help drive improvement for pupils and teachers
- Make sure the school is keeping up with external best practice and innovation

Figure 2. Life without Levels

Ethical considerations must also be accounted for. No prior agreement, with the student or their legal guardians, will exist to cover the collection of learning data for the new purposes of analysis. While the decisions taken following analysis will be educator driven, the results of the analysis will inform those decisions. Students and parents should therefore be made aware of, and provide their consent for: the data that is being collected, the purpose of the analysis, and the manner with which it is dealt.

TECHNOLOGY-SUPPORTED LEARNING PILOT

During 2014/2015 we ran a pilot implementation in The Whitehaven Academy, Cumbria. Within this Academy, the pilot focused on one Year 9 class across three curriculum areas: English, Science, and ICT.

The objectives and success criteria were set out at the beginning of the project and covered not only objectives around learning analytics itself, but also the devices, staff continual professional development (CPD), and the methods for constructing and delivering the personalised learning pathways to students.

Students were surveyed at the beginning of the process and at the end of the process; the survey captured sentiment, attitudinal information and perceptions about capability. The project also included surveys on use of devices, along with analysis of usage, dialogue interaction and results.

During this proposed Technology Showcase, we will share the pilot objectives, findings, successes and the lessons learnt.

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Figure 3. BYOD at The Whitehaven Academy

TECHNOLOGY SHOWCASE

We intend to demonstrate live the connected platform of tools used during the pilot implementation and for the full roll-out across the Trust.

We will supply 30 tablet and mobile devices for the purposes of the showcase, and allow those present to interact in a meaningful way with their devices.

We will take these participants on a journey that reflects the pilot journey:

- Constructing the content and knowledge rubrics, assessments and learning pathways.
- Using technology to engage in feedback and dialogue, captured in a way that can support analysis, and monitoring the completion of learning pathways.
- Using tools to understand progress in learning, issues, attainment and warning signs of non-completion.
- Setting learning analytics in the context of academic analytics and other student factors recorded – to provide a holistic data picture of the child.
- Addressing peer (both student and staff) collaboration, sharing and dissemination.

These tools form part of a cohesive whole, and we address both technical and user experience considerations from security to single sign-on. The majority of the tools we demonstrate are free to use in education worldwide, and could be deployed quickly by any member of the audience.

LESSONS LEARNT AND WHERE NEXT?

Our technology demonstration will be the mode by which we present the pilot objectives and success criteria and provide the context to discuss the key lessons learnt during the process in order that others can benefit.

Lessons have been learnt at all stages of the learning analytics project – from setting a clear vision and

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objectives, selecting the scope, and involving participants early, through to methods and approach for data collection, compilation, analysis, dissemination and impact on the continuing professional development (CPD) of staff involved. We are continuing to learn lessons as we move to scale across the Multi-Academy Trust – especially in an environment that has a lack of defined standards in this area.

As we move to a larger scale, we also continue to work on extending the technical scope to perform more meaningful analysis that can be predictive and prescriptive. We are now using AzureML as a cloud-based machine-learning environment to provide such feedback within our system and are considering more personal student data collection forms and feedback loops in the form of wearables.

Policies and ethics surrounding this area are currently unformed in our context – and so we will continue to attempt to contribute to moving these forward.



Figure 4. The Principal and the Senior Leadership Team at the Academy

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Showcase

Architecting a scalable Open Learning Analytics Cloud platform

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Jisc, through its Effective Learning Analytics initiative is funding the world's first national-level analytics deployments to deliver flexible learning analytics service for UK universities. Marist College and Unicon Inc., the members from the Apereo Learning Analytics Initiative (LAI), are architecting key components of this Open Learning Analytics platform which includes: (a) a Learning Analytics Processor (b) an Open Dashboard and (3) an Intervention system. These systems leverage multi-institutional learner data collected in a Learning Record Warehouse operated by Jisc and its vendors. The technical showcase demonstrates the cloud-based solution containing the learning analytics components working as a cohesive system.

DEPLOYMENT

By the time of the presentation, a UK-specific baseline Predictive Model will be available and a majority of technical work completed on the cloud-based scalable learning analytics service.

The technical demonstration plans for its audience to:

- Gain a solid understanding of components that form Open Learning Analytics Framework and its strategic vision
- Gain knowledge about emerging Open standards and interoperability platform
- Gain insights on technical strategy and decisions.
- Benefit from lessons learned in building and deploying such a system
- Seek better collaboration opportunities to propel the open analytics platform effort
- Interest developers, educators and researchers

EFFECTIVE LEARNING ANALYTICS INITIATIVE

Through its Effective Learning Analytics initiative, the Jisc is funding and supporting one of the world's first national-level learning analytics deployments with the goal of developing a sustainable and flexible learning analytics service for UK universities and college. Over the course of the first year of this initiative, a range of research was conducted by the Jisc to survey the learning analytics landscape as a

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means to develop a vision and plan for this pioneering effort. The result was a modular technical architecture that included the following components as shown in Figure 1:

1. **Learning Analytics Processor** – Designed to accelerate the future of open predictive learning analytics, this flexible and highly scalable analytics tool facilitates everything from academic early alert systems to data visualizations through an ‘app store’ architecture.
2. **Staff Dashboard** – OpenDashboard is a web application that provides a framework for the development of reports and data visualisations. It is designed specifically for a learning context with support for standards such as the Learning Tools Interoperability specification developed by IMS Global Learning Consortium (IMS LTI) and the Experience application program interface known as xAPI.
3. **Learning Record Warehouse** – A service to store activity data (in xAPI format), as well as data about the students, their courses and their achievements and grades.
4. **Alert and Intervention System** – The Student Success Plan is web-based holistic counselling and intervention software designed to increase the persistence, success, and graduation rates of the at-risk student.
5. **Student Consent Service** – A service that allows students to control how their personal data is used, for example controlling who can see and use self-declared data, as well as giving some control over the types of intervention and support they would like to receive.
6. **Student App** – An app, inspired by fitness trackers, that helps students improve their learning through the use of analytic data. As well as taking data from the learning records warehouse, the app will allow students to add their own data (self-declared data), for example recording how long they study, read and so on.

In addition to these components, the architecture calls for the use of open standards and API to facilitate data extraction from multiple sources including the virtual learning environment (VLE) or learning management system (LMS), student information system (SIS) and library systems, as well as self-declared data.

Following the developing of this vision and architecture, the Jisc issued a tender in early 2015 with the goal of contracting with suppliers to provide UK institutions with two solution options, one being based on proprietary vendor-based software and the other being a completely open-source solution. This technical showcase will discuss the development and deployment of the open-source solution undertaken by Marist and Unicon, which primarily leverages the work of the Apereo Learning Analytics Initiative (Apereo LAI). All the work will be released under open licences, allowing institutions globally to benefit from and build on it.

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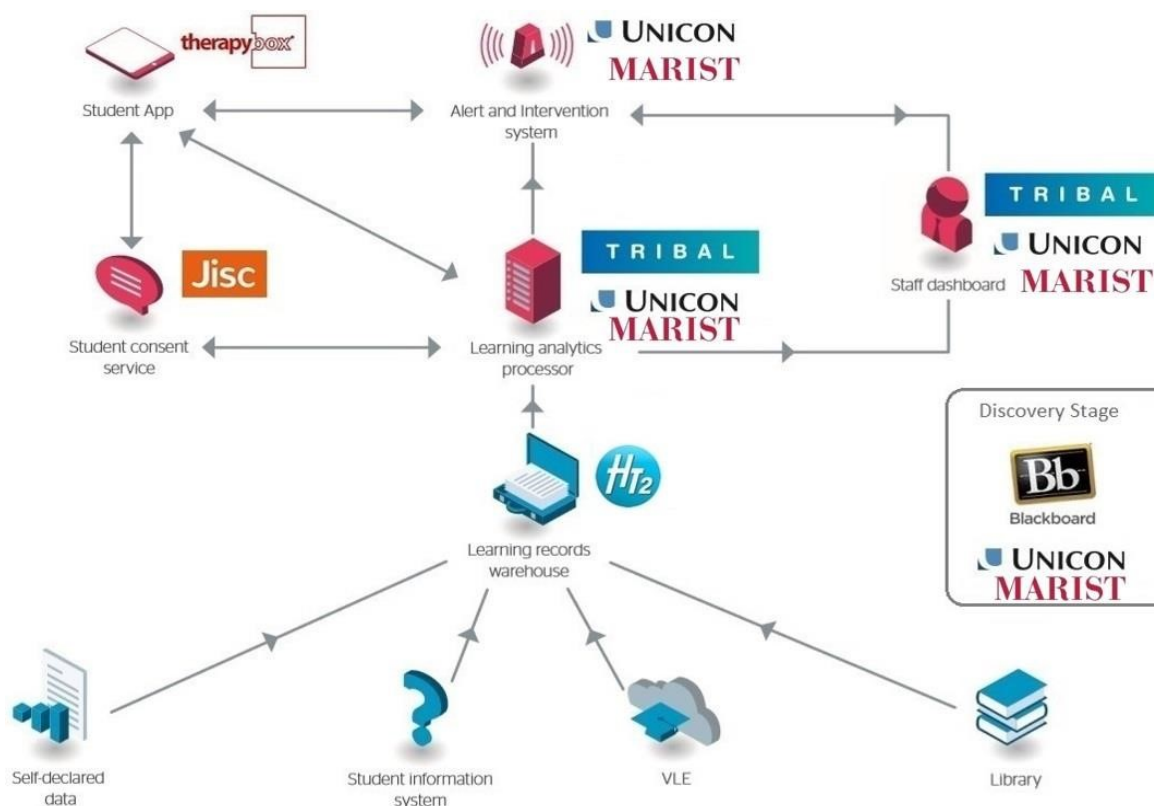


Figure 1. Jisc's learning analytics architecture

In 2014, Apereo LAI was started by Marist College, Unicon and University of Amsterdam with a unified vision of creating an open-source platform for learning analytics. The team developed the Apereo LAI Diamond architecture, which includes the following components:

Learning Activities Collection

- Implementation of learning analytics specifications (xAPI, IMS Caliper) in existing systems, such as learning management systems (LMS)

Learning Record Storage

- Integration of learner interaction systems with activity collection systems
- Development and/or implementation of learning record stores (LRS) and managed services

Learning Data Analysis

- Automation of learning analytics model processing
- Development of learning analytics models

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Analytics Results Action and Communication

- Development of the presentation and visualisation of the analytics output (for example, dashboards)
- Integration with student success applications

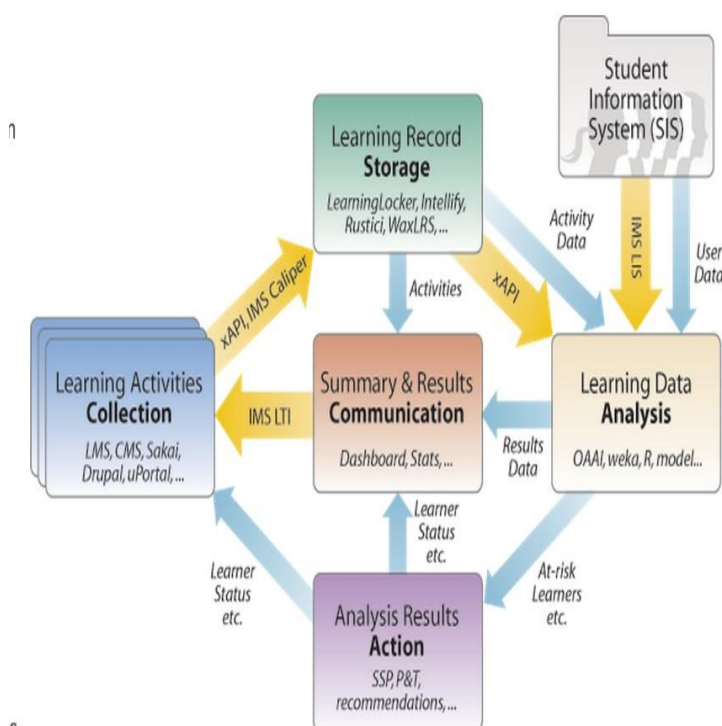


Figure 2. Aperoe LAI Diamond Architecture

The Jisc vision of delivering a national-level learning analytics solution and Aperoe LAI's focus on an open platform formed a natural partnership to develop an open cloud-based Learning at Scale solution. The components that will be showcased include the following Aperoe-endorsed projects

LEARNING ANALYTICS PROCESSOR (LAP)

The LAP is an open-source web application that provides a framework the execution of analytics pipelines. The analysis workflow is generally referred to as a pipeline and consists of three distinct phases: input, model execution, and output.

- Inputs phase – typically involves extraction, transformation and loading (ETL) of data from one or more data sources such as learner data from a LRS (event data), a SIS (student, course data), and possibly an LMS (grade data).
- Model Execution – Once all of the data sources have been transformed into the appropriate format and loaded into the processor, the next phase is execution of a pre-built analytics predictive model. Models are often represented in Predictive Model Markup Language (PMML),

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an XML-like format, and execution is often handled by a third-party library such as Weka or Apache Spark.

- Outputs phase – aggregates the results of the model execution and typically passes the results to the file system or a data store and exposes them via web service APIs. Currently, the LAP supports the Marist OAAI Early Alert and Risk Assessment models but development of additional models for the Jisc as well as scalability enhancements are underway.

OPEN DASHBOARD

A web application that provides a framework for displaying visualisations and data views called ‘cards’. Cards represent a single discrete visualisation or data view but share an API and data model. These data views can be arranged to create a configurable Dashboard. Open Dashboard is compliant with the learning tools Interoperability specification developed by IMS Global Learning Consortium (IMS LTI).

STUDENT SUCCESS PLAN (SSP)

The open-source SSP case management software supports a holistic coaching and counselling model that expedites proactive interventions for students in need. SSP enables counsellors to manage their caseloads effectively. It features tools advantageous to counsellors, including a Journal for comprehensive note taking and academic planning.

The aim of this multi-institutional, inter-disciplinary Jisc/Aperio technical demonstration is to share experiences in integrating the systems that form the Open Learning Analytics platform. By building software artefacts that have shared requirements fitting into a consistent framework and emphasising interoperability and standards, we hope to support practical innovation, channel effort, ease barriers to adoption and further enrich the platform.

Showcase

Early Intervention System for Student Success

Shady Shehata

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In this work, we describe a Student Success System (S3) that can measure student performance, starting from the first weeks of the semester. S3 is an early intervention system that empowers institutions with predictive analytics to improve student success, retention, completion and graduation rates. S3 provides educators with early indicators and predictions of student success and risk levels. Predictions generated by S3 are based on predictive models that are created by applying machine-learning algorithms to historic course data. The predictive models are adaptable and customisable to the instructional approach of each course, as well as engagement and achievement expectations.

DEPLOYMENT

A university and a higher education college partnered with D2L to begin piloting the Student Success System. The system was deployed in production and testing environments to serve three campuses. A list of pilot courses has been chosen for each institution. For each pilot course, model criteria and historical course data was gathered, domain configurations were created, and models were built in simulation mode. After running S3 for multiple semesters, model evaluation experiments have been conducted to measure the S3 accuracy, as shown in the results section.

STUDENT SUCCESS SYSTEM

The core component of the Student Success System is the prediction engine, which is able to generate a customised predictive model for an individual course. On the main page of the student success system, instructors can monitor the status of each student in terms of their predicted success (Figure 1).

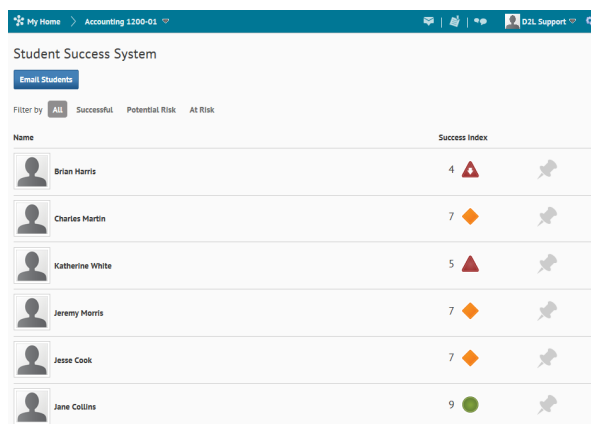
For each student, a Success Index is displayed for the current week. The success index is expressed as a category, a corresponding score on a scale of 0-10, and trend sign as shown in Figure 2.

There are three levels of success indicated by the colour and shape of an associated symbol: At-Risk (red triangle), Potential Risk (yellow diamond) and Successful (green circle). The levels are determined based on thresholds for the predicted grade. The defaults are: 0%-60% for At-Risk, 61%-80% for Potential Risk and 81%-100% for Successful.

From the Instructor Dashboard, an instructor can initiate a group intervention based on success category via email. An email dialogue will pop up with all student addresses in the Bcc field as shown in Figure 3.

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


Name	Success Index
Brian Harris	4 
Charles Martin	7 
Katherine White	5 
Jeremy Morris	7 
Jesse Cook	7 
Jane Collins	9 

Figure 1. Student dashboard

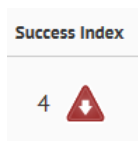
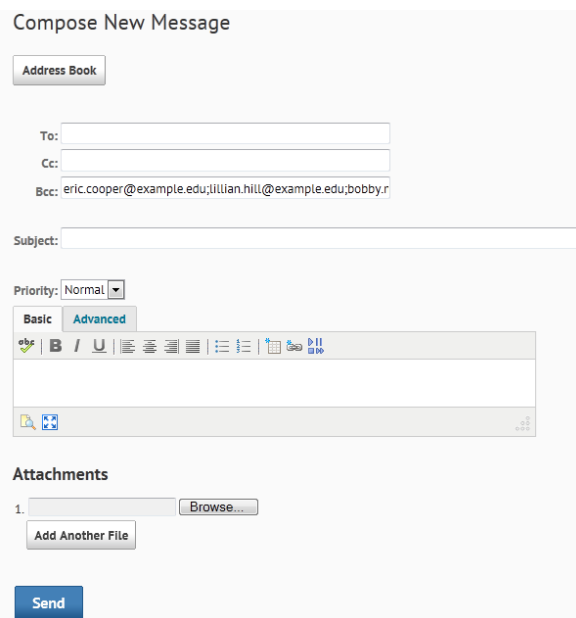


Figure 2. Success Index icon



Compose New Message

Address Book

To:


Cc:

Bcc: eric.cooper@example.edu;lillian.hill@example.edu;bobby.r@example.edu

Subject:

Priority: Normal

Basic Advanced



Attachments

1.

Figure 3. Email student intervention

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The instructor can choose to drill down on an individual student to gain the insights the instructor needs about the individual student, so that the instructor can design a personalized intervention.

S3 PREDICTIVE ENGINE

Traditional/statistical regression procedures are often identified as the processes deriving a function $f(x)$ that has the least deviation between predicted and experimentally observed responses for all training examples.

Regression Analysis

One of the main characteristics of Support Vector Regression (SVR) is that, instead of minimising the observed training error, SVR attempts to minimise the generalised error bound in order to achieve generalised performance. This generalisation error bound is the combination of the training error and a regularisation term that controls the complexity of the hypothesis space.

The S3 Predictive engine uses SVR to predict student performance starting from the first weeks of the semester. The S3 predictive engine generates a customised predictive model for each individual course rather than having one model for all courses. The output of the predictive model is the success index.

Figure 4 shows the administrative part of the system where the configuration of the predictive model can be adapted to each course by the S3 administrator. It shows the selection of 'Domains' (predictive components of the model), the range for the success levels and the historical offerings of the course that can be taken as representative of the current offering of the course for which the predictions are generated.

The S3 predictive engine generates regression models for each course. The success index generated by the regression model can be aggregated either by the domain or by the feature.

S3 has advanced model options for advanced users who wish to experiment further with model tuning. A number of options can be modified from recommended settings. There are two options: model aggregation and data extraction.

The model aggregation option determines the type of aggregation for calculating the success index. The default and recommended setting for the success index are calculated by aggregating the indicators associated with each domain. The domain indicators represent the success / risk outcome based on the set of measurements related to each domain. An alternative aggregation formula is for the success index to be determined based on variables without the pre-defined grouping of variables into domains.

Configure Predictive Model for Biology 1100-01

Select Model Domains

In order to make predictions that include the Preparedness domain you must upload student information system data prior to running the predictive model.

Domains

- ☒ Success Index
- ☒ Course Access
- ☒ Content Access
- ☒ Social Learning
- ☒ Grades
- ☒ Preparedness

Advanced Model Options >

Confirm Biology 1100-01 Details

Start of Grade Range (%)

0 ▲ At Risk

60 ◆ Potential Risk

80 ● Successful

Start Date End Date

11/31/2011 11/31/2011

Student Roles

End User ✎

Map Historic Courses

Add Course

Course Name	Start Date	End Date	Student Roles	
Cell Biology Lab	11/7/2012	11/7/2012	End User ✎	✕
Fundamentals of Microbiology	11/7/2012	11/7/2012	End User ✎	✕

Save and Continue Close

Figure 4. Model admin page

Domain Aggregation

At the stage of domain aggregation, the success index is generated in two steps. First, each domain model generates predictions based on the domain features. Then the overall domain generates the overall success index based on the output of each domain model, as shown in Figure 5.

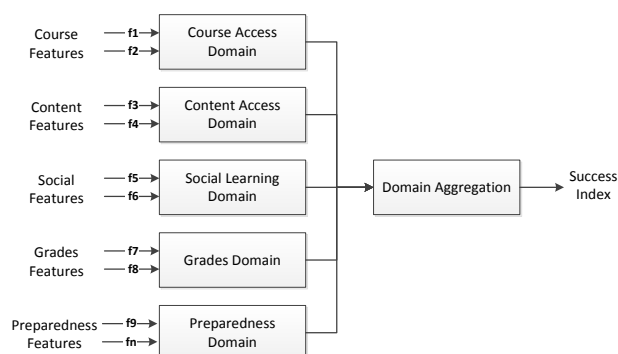


Figure 5. Domain aggregation

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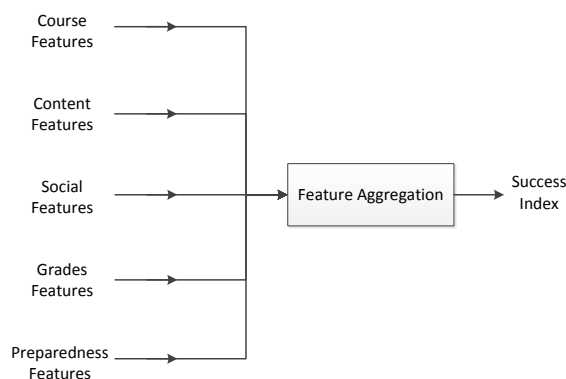


Figure 6. Feature Aggregation

Feature Aggregation

At the feature aggregation stage, the success index is generated in one step where the features of all domains are used to generate the overall success index, as shown in Figure 6.

Results

In regression analysis, ‘mean squared error’, referred to as ‘mean squared prediction error’ or ‘out-of-sample mean squared error’, can refer to the mean value of the squared deviations of the predictions from the true values, over an out-of-sample test space, generated by a model estimated over a particular sample space. This is also a known, computed quantity, and it varies by sample and by out-of-sample test space.

Experiment

Two higher education institutions, a university and a college, are the early adopters of the Student Success System (S3). After S3 had run for two semesters at both institutions, we used the generated predictions and actual final grades to calculate the average MSE (the lower the better) for 45 courses in the university and 36 courses in the college. We also calculate the average of the MSE for each week across all courses at both as shown in Figures 7 and 8 and Table 1. In the figures, the x-axis is the week number and the y-axis is the MSE.

Table 1. Average MSE over courses

Institution	Number of Courses	Number of Students	Average MSE%
University	45	5768	12%
College	36	1270	14%

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For the university, the analysis was applied to 45 courses included 5768 students. The average MSE over 45 courses was 0.12. The average MSE over weeks started in the first week at 18% and went down to 2% in the 21st week. As shown in Figure 7, the low values of MSE demonstrate the quality of the predictions generated by S3.

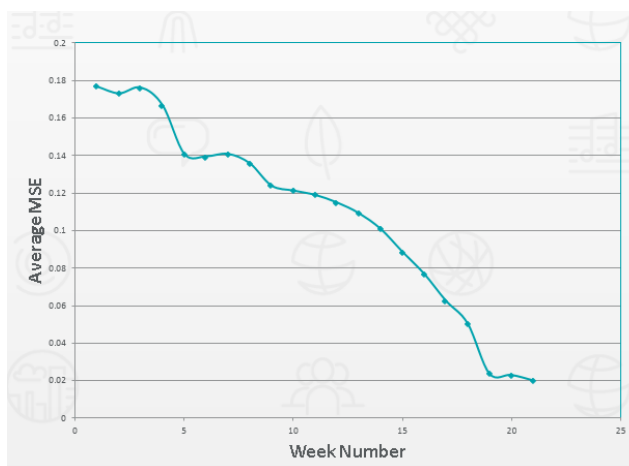


Figure 7. University results – average MSE over weeks

For the college, the analysis was applied to 36 courses that included 1,270 students. The average MSE over 36 courses was 0.14. The average MSE over weeks started in the first week at less than 20% and went down to almost 1% in the 17th week, as shown in Figure 8.

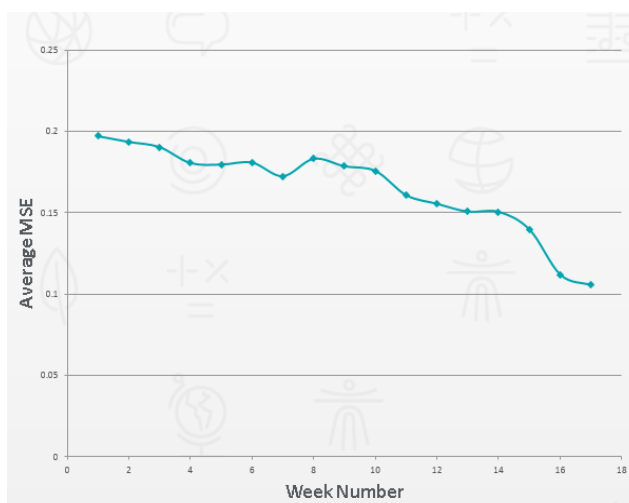


Figure 8. College results – average MSE over weeks

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Model Domain Comparison

We compared the models built for each institution, taking into account the different characteristics of the two institutions.

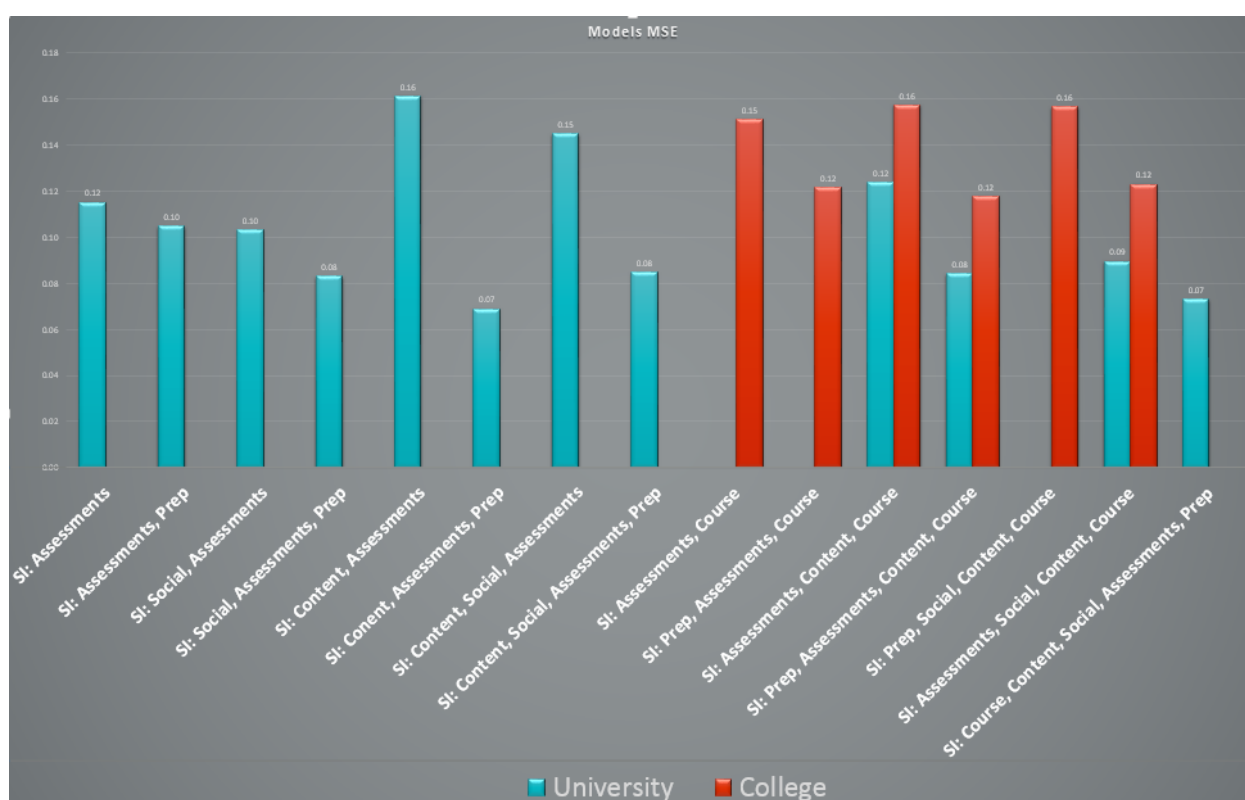


Figure 9. Model domain comparison

As shown in Figure 9, a combination of domains is commonly used in both institutions, including Assessments, Content, and Course Access. This analysis shows that the S3 predictive engine is able to customize high quality predictive models for individual courses.

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Showcase

Coh-Metrix in the Cloud: Lessons from Implementing a Web-scale Text Analytics Platform

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An overview of a recent project to re-implement the Coh-Metrix text analysis tool as a web-scalable text analytics platform. I will present the new system, its features, and some of the technology used to implement it. I will demonstrate how a small team with limited resources can nevertheless leverage cloud computing to achieve startling analytics performance on big data. I will present some of the lessons learned during the implementation and best practices for others aiming to make use of these technologies.

DEPLOYMENT

I will present feedback from beta testers and other early users of the new platform, including performance statistics on how quickly they were able to process large data sets.

COH-METRIX

The Coh-Metrix text-analysis tool has been at the cutting edge of text and discourse analytics for many years (Graesser, et al., 2004; McNamara, et al., 2014). It has been used successfully in learning analytics and educational data-mining research projects to analyse student discourse and learning (Dowell, et al., in press). Historically, however, it has suffered from performance bottlenecks and usability issues, which has limited its use to a relatively small group of researchers and small-to-moderate datasets.

Natural language processing (NLP) is complex and computationally intensive. In order to leverage its potential to analyse the vast amounts of unstructured text data being generated in online learning environments requires web-scalable computational platforms. The recent growth in the availability of cloud-computing platforms and cluster-computing programming has opened up new possibilities for detailed and sophisticated analysis of vast stores of text.

In 2014, the Fedex Institute of Technology at the University of Memphis hired me to lead a project to transform Coh-Metrix into such a web-scalable analytics platform. I propose to demonstrate the power of this new text analytics web service, present some important lessons learned from the implementation, and guide users through how they might make use of the system in their own research.

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In the world of big-data analytics, simply upgrading hardware is insufficient to the task. The data-centre has become the new computer, and both data and processing must be distributed across clusters of computers. Coordinating and managing these computational clusters is complex and difficult. In my presentation, I will show how we made use of Amazon's cloud computing services and the Spark cluster-computing framework (Zaharia, et al., 2010), to build a web-scalable text analytics system. These tools automate a great deal of the tricky work of system coordination and management in massively parallelised architectures, and allow even a small team to make use of the vast amounts of computing power now available in cloud platforms.

I will specifically focus on Spark's machine-learning pipeline system, which has been central to the development of Coh-Metrix in the cloud, and on Amazon's Elastic MapReduce service, which makes it easy for anyone to set up and deploy cluster-computing programs to process data across tens or hundreds of computers. This combination of tools has enabled us to increase the processing speed of Coh-Metrix by more than three orders of magnitude.

Making a data-analytics tool accessible is not just about having a pretty interface or website. The system must be accompanied by data-management services that enable the tool to be used effectively. I will give an overview of the kinds of services we have built to store and manage text data, as well as ancillary services such as text extraction and cleaning. I will discuss how these are stored in cloud data stores, and the kinds of design decisions made to choose the right solutions for each type of data. I will also give an overview of systems we have designed that allow users to create and submit text-analytics tasks, and to share data and results with teams of colleagues and collaborators.

I aim to provide an engaging presentation for both researchers hoping to make use of the new Coh-Metrix facilities in their research and for technologists and engineers who may wish to implement some of the same techniques to scale up their own analytics tools.

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